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Potatoes Leaf Disease Detection through Naïve Bayes, JRip, and Decision Stump with BPPF and ACCF models

Revathy M[1], Dr. Karthikeyan Elangovan[2]

[1]Research Scholar (Part time Internal), Department of Computer and Information Science, Annamalai University, Annamalai Nagar, India.

[2]Research Supervisor, Assistant Professor/Programmer, (Deputed as Assistant Professor and Head in Government Arts and Science College,Gingee,Villupuram), Department of Computer and Information Science ,Faculty of Science, Annamalai University, Annamalai Nagar, Tamilnadu, India.

Email ID: revathimphil1213@gmail.com

Email ID: kanchikarthi2010@gmail.com

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ABSTRACT

Plant diseases constitute a critical challenge to global agricultural systems, leading to substantial economic losses and threatening food security. The early detection and accurate identification of plant diseases are essential components for achieving sustainable crop production. *Solanum tuberosum* (potato) is among the most widely cultivated and economically important crops worldwide, yet it remains highly susceptible to a variety of pathogenic infections, particularly foliar diseases. Early-stage identification and precise classification of leaf diseases are crucial for implementing timely management strategies and minimizing yield losses. Accurate disease classification not only aids in effective crop protection but also contributes to overall agricultural resilience. In this study, we propose a deep learning-based model specifically designed for the classification of potato leaf diseases, aiming to enhance early detection capabilities and support decision-making processes in precision agriculture. The research introduces a time-efficient disease classification framework that utilizes BPPF and ACCF feature extraction methods together with Naïve Bayes and Decision Stump and JRip classifiers running on WEKA 3.9.5 platform. The evaluation standard utilized the Kaggle dataset consisting of 1500 labeled images that covered 3 different classes of healthy and diseased leaves. A standardization process was applied to the input data through image resizing and normalization with additional augmentation techniques. The classifiers received training through extracted features from BPPF and ACCF while their performance evaluation used Accuracy, Precision, Recall and ROC-AUC, PRC-AUC along with Execution Time metrics. BPPF combined with Naïve Bayes classifier established 97.28% accuracy while ACCF and Naïve Bayes achieved 97.02% accuracy during 0.02 seconds of execution time. JRip-based models achieved high precision and recall numbers though their computational expenses remained high whereas Decision Stump models operated fast yet gave inferior classification accuracy results. Naïve Bayes classifiers operated with BPPF and ACCF descriptors reveal themselves as highly effective tools for real-time plant disease diagnosis in agricultural settings through their fast execution and interpretable method.

Keywords: *Naïve Bayes, JRip, Decision Stump, Feature Engineering, BPPF, ACCF, Classification, Pattern Recognition, Performance Metrics, Real-time Machine Learning*

1. INTRODUCTION

The potato (*Solanum tuberosum*) is one of the most extensively cultivated crops worldwide and serves as a critical food source for millions of people. Despite its importance, potato cultivation is highly vulnerable to a range of diseases, particularly foliar diseases, which can markedly reduce both yield and crop quality. Early detection and accurate diagnosis of leaf diseases are essential for effective disease management and the prevention of pathogen spread. Traditionally, disease diagnosis has relied on visual inspection by trained experts, wherein agronomists or farmers assess potato plants and tubers for characteristic symptoms such as leaf spots, discoloration, and wilting, indicative of diseases like late blight and early blight. However, these manual inspection methods are time-consuming, labor-intensive, and subject to human error. Recent advances in machine learning and computer vision technologies have introduced promising alternatives for plant disease detection, offering the potential for faster, more accurate, and scalable diagnostic solutions. Plant diseases create a major threat to worldwide food security because they hurt crop production along with crop quality within different agricultural systems worldwide. Fast detection accompanied by precise diagnosis of plant diseases constitutes the main foundation for reducing their consequences and initiating successful treatment methods. Manual identification techniques prove time-consuming because they need expert knowledge and they experience human errors when experts need to differentiate visually similar symptoms. The Plant Village dataset provides scientists with an extensive collection of labeled plant leaf pictures that enables the development of effective intelligent classifying systems. Research into lightweight feature-based classification techniques stands essential because these methods provide both fast and inexpensive solutions as well as explainable outcomes. This research implements Auto Color Correlogram Filter (ACCF) alongside Binary Patterns Pyramid Filter (BPPF) to extract significant features which are accompanied by lightweight classifiers running in WEKA version 3.9.5 for effective plant disease classification. Spatial color relationships from ACCF generate vital chromatic patterns that detect disease manifestations. BPPF utilizes Local Binary Patterns (LBP) pyramids to analyze textures at different resolutions which detects both subtle and large-scale structural indicated plant stress symptoms. The processing steps of size adjustment normalization and data augmentation transformed the extracted features which later supported training and assessment of Naïve Bayes JRip and Decision Stump classifiers. Multiple classifiers were chosen because their straightforward operations provided an interpretable framework which supported feature-based methodology. The research utilizes this method to prove that precise plant disease diagnosis is possible without deep learning models which enables use in agriculture applications for resource-limited production settings. The accuracy classification evaluation combines Precision and Recall measures with F1-Score to identify optimal configurations. The article divides its content into three parts including section 2 for literature survey followed by section 3 which implements materials and methods and section 4 presents results with discussions before concluding in section 5.

2. LITERATURE SURVEY

Modern plant health monitoring systems focus on producing light-weight accurate scalable models which manage to detect unusual patterns across various plant species alongside their diseases. The research from Wang et al. [1] presents LeafMamba as a new IoT-enabled network which absorbs multiple data scales to enhance detection precision through minor computational demands. A combined system of Segment Anything Model (SAM) and a custom CNN architecture allows Balasundaram et al. [2] to achieve 95.06% accuracy in identifying Algal Spot and Brown Blight diseases on tea leaves. Thai et al. [3] developed EF-CenterNet as an anchor-free detection model using EfficientViT and feature pyramids to process dense banana leaf disease scenarios while maintaining high precision and lowering the model parameters. Bouacida et al. [4] developed a generalized CNN-based detection system that recognized plant diseases in unseen crops after scanning specific infection regions instead of complete leaf morphology with 97.13% generalization accuracy. Ning and colleagues [5] applied modifications to YOLOv8 which enhanced its efficiency for determining corn leaf counts in outdoor conditions thus emphasizing lightweight detection models' role within precision farming. The research team of Wang et al. [6] presented a programmable YOLOv9 model that revolutionized gradient-based learning which improved how well the system worked with different plant disease datasets. The authors of [7] performed DETR model optimization for complex rice leaf disease detection problems while improving their ability to model relationships across long distances in data. Research conducted by Mora et al. [8] utilized UAV aerial imaging to identify Banana Xanthomonas Wilt and proved that aerial systems work well for agricultural disease identification. Bouacida et al. [9] stressed deep learning models deal with problems in generalization and robustness because of the wide range of plant species and varied environmental factors. NVIDIA's TensorRT optimizer tools [10] present deployment optimizations which boost the inference speed for agricultural workloads.

YOLOv5 demonstrated its effectiveness in detecting bell pepper diseases when Mathew and Mahesh applied it to field conditions according to their research [11]. The research of Amarasingam et al. [12] compared YOLOv5 with DETR and Faster-RCNN systems for detecting sugar cane leaf diseases and established the superiority of YOLOv5 in terms of achieving speed alongside precision. The research community adopted Vision Transformers when Sun et al. [13] presented SE-ViT which integrated self-attention methods for superior sugarcane and tea leaf disease recognition. An increasingly popular trend involves designs that integrate CNNs together with Transformer modules. The research team of Sun et al. [14] created ConvViT which merges self-attention blocks with convolutional building blocks to establish a robust multi-crop disease classification system. The research by Ye et al. [15] demonstrates how Hyperspectral UAV imaging in banana disease detection becomes more effective when combined with deep learning techniques through multispectral sensing. The detection of sugarcane diseases through multispectral UAV imagery gained success using Random Forest and XGBoost classifiers which achieved competitive performance levels according to Narmilan et al. [16,32-35]. The research done by Mallick et al. [17,36-38] showed that CNN architectures excel at groundnut disease detection thereby confirming deep models' effectiveness in small crop applications. The PSPNet model operated with 98% accuracy for detecting yellow rust in wheat crops through its analysis of UAV acquired images according to Pan et al. [18]. The research by Bouacida et al. [19] demonstrated that models become transferable for new disease scenes when trained on datasets such as Plant Village through generalized model cross-validation. Research by Thai et al. [20] established that anchor-free models particularly EF-CenterNet demonstrate superior scalability together with practical field applications when compared to traditional anchor-based detection architectures and other related machine learning models on agricultural and environment [21-23,28-31]. Agriculture has long relied on scientific advancements to satisfy global food needs. However, various challenges encountered by those in this industry endanger the food security of human society. Recognized risks include shifting climate patterns, the impact of livestock grazing, the spread of plant diseases, and more (25).Diverse methods, including image processing, ML, and DL, have been used to monitor and detect plant diseases, leading to substantial progress (26). A K-means clustering segmentation technique has been employed for disease identification on potato leaves. This approach extracts features from image samples like area, color, and texture. Subsequently, algorithms based on neural networks are employed to classify and recognize diseases (27).

3. MATERIALS AND METHODS

Dataset Description

This dataset is basically taken from this source that contains 1500 image files of 3 different classes, namely early blight, late blight, and healthyimages.

(https://www.kaggle.com/abbasataiemontazer/potato-leaf)

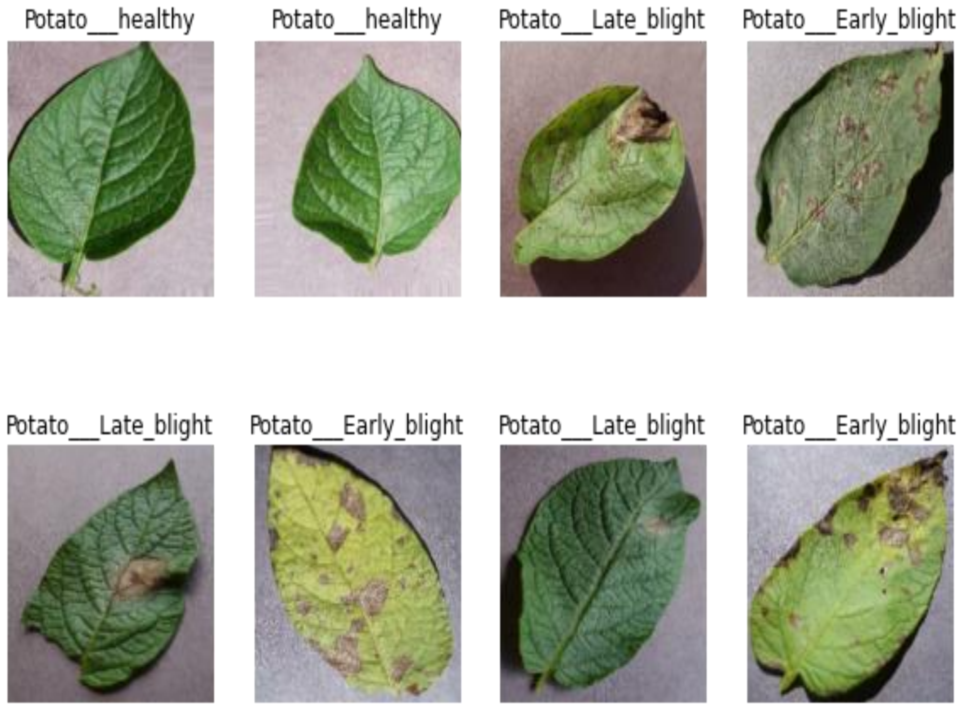


Figure 1: Example images of potato leaves: Early blight, Late light, and Healthy

The images were taken under controlled environmental settings which included plain backgrounds together with uniform lighting as well as centered leaves to minimize external noises and highlight disease symptoms.

Preprocessing

The preprocessing phase included multiple steps that standardized the data structure while preparing it for feature extraction before training the model. All images received resolution normalization to 128 × 128 pixels as a first-step. The dimension reduction decreased computing costs without sacrificing the vital structural characteristics along with the necessary textural information needed for disease detection. Min-Max normalization was applied to pixel values to normalize them into the range between 0 to 1. By performing this normalization process all features received equal scaling which prevented training bias that would occur because of varying attribute sizes. To enhance model robustness and account for intra-class variability, minor augmentation techniques were applied, Horizontal and vertical flipping, Small rotations (±15 degrees), Random zoom and shifts These augmentations expanded the effective training set and improved generalization to unseen samples, Pre-processed images were systematically prepared for feature extraction via: Auto Color Correlogram Filter (ACCF): capturing spatial color relationships, Binary Patterns Pyramid Filter (BPPF): capturing multi-resolution texture patterns. The preprocessing outcome produced a standardized image collection that optimized both feature extraction speed and accuracy before generating an ARFF file for WEKA-based classifier instruction.

Feature Extraction Techniques

Two handcrafted image descriptors were used:

- **Binary Patterns Pyramid Filter (BPPF)**: Extracts multi-resolution texture features using Local Binary Patterns (LBP). For a pixel *p*, the LBP is defined as:

$\mathbf{LBP(p) = \Sigma\ [sign(I_n - I\_p) \times 2^n]}$,where I_p is the center pixel intensity and I_n are its neighbours. Multi-level feature pyramids help capture both fine-grained and coarse texture structures.

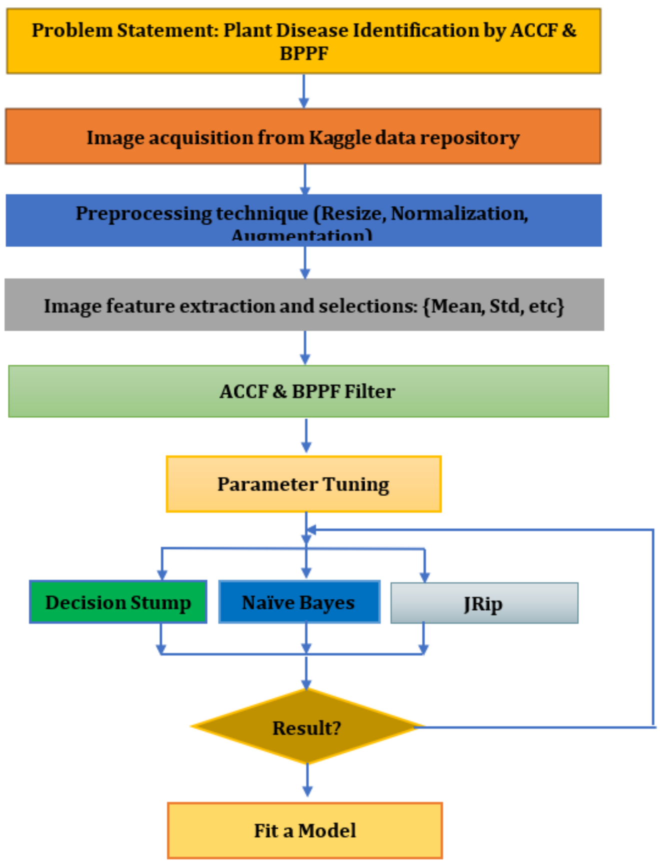
- **Auto Color Correlogram Filter (ACCF)**: Encodes color spatial correlation by computing the probability $\mathbf{P(c_1, c_2, d)}$ that a pixel with color c_2 appears at a distance d from a pixel of color c_1. This descriptor represents both color and spatial information.

Classification Techniques

The following lightweight classifiers were applied using **WEKA 3.9.5**:

- **Naïve Bayes (with BPPF and ACCF)**: A probabilistic classifier based on Bayes' theorem with the assumption of feature independence. For a given feature vector $X = \{x_1, x_2, \ldots, x_n\}$, the posterior class probability is computed as:$\mathbf{P(C|X) \propto P(C) \times \Pi\ P(x_i|C)}$,where $P(C)$ is the prior, and $P(x_i|C)$ is the likelihood of the feature x_i given class C.
- **JRip (with BPPF and ACCF)**: Implements the **RIPPER algorithm**, a rule-based learner that iteratively builds and prunes classification rules. It is well-suited for interpretable models. A rule takes the form:**If condition$_1$ ∧ condition$_2$ ∧ ... then class = C**,where the conditions are threshold-based checks on feature values.
- **Decision Stump (with BPPF and ACCF)**: A single-level decision tree classifier. It selects one feature *f* and a threshold *t* to split the dataset using the rule: **If $f \leq t$ then class A else class B**.Though simple, it serves as a strong weak learner for boosting and provides a baseline for evaluating feature separability.

All classifiers were trained using **10-fold cross-validation**, and data was formatted into **ARFF files** for compatibility with WEKA. Classifier modules were selected from the respective categories: bayes for Naïve Bayes, rules for JRip, and trees for Decision Stump.



NO

Yes

Figure2: Proposed System

Evaluation Metrics

Each classifier-filter pair was evaluated using the following metrics:

- **Accuracy = (TP + TN) / (TP + FP + FN + TN)**
- **Precision = TP / (TP + FP)**
- **Recall = TP / (TP + FN)**
- **F1-score = 2 × (Precision × Recall) / (Precision + Recall)**

These metrics enabled comparative analysis of classification performance and were used to identify the most effective filter-classifier configuration for skin disease image classification.

4. RESULTS AND DISCUSSION

Six handcrafted techniques are evaluated together with the selected classifier to determine their effectiveness in multiclass skin disease classification. Evaluation of the models happened according to accuracy, precision, recall, ROC AUC, PRC AUC and execution time metrics.

Table 1: Classification Metrics

Classifier	Accuracy	Precision	Recall	ROC	PRC	Time
BPPF+Naive Bayes	97.28%	0.97	0.97	0.99	0.98	0.03
ACCF+Naive Bayes	97.02%	0.97	0.97	0.97	0.96	0.02
BPPF+JRip	96.77%	0.97	0.97	0.97	0.95	1.09
ACCF+JRip	96.91%	0.97	0.97	0.99	0.99	1.13
BPPF+Decision Stump	92.02%	0.92	0.92	0.94	0.95	1.04
ACCF+Decision Stump	91.16%	0.91	0.91	0.93	0.93	0.14

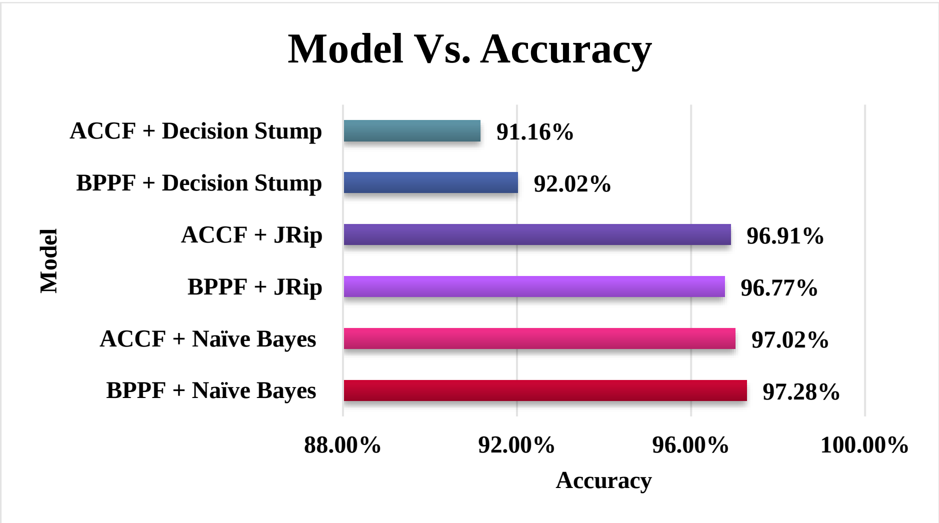


Figure 2: Model Vs Accuracy

The above figure 3 shows BPPF+Naïve Bayes delivered the maximum accuracy level at 97.28% because its strong capability to recognize patterns within BPPF features. The Naïve Bayes classifier displays exceptional compatibility with both ACCF and Naïve Bayes features according to their accuracy score of 97.02%. This shows the suitability of the Naïve Bayes algorithm for making probabilistic decisions with these features. The accuracy results for both ACCF+JRip and BPPF+JRip stood as 96.91% and 96.77% respectively. The JRip rule-based classifier delivers excellent performance when working with either feature description but achieves results that marginally trail the Naive Bayes algorithms. BPPF+Decision Stump alongside ACCF+Decision Stump produced the least accurate results at 92.02% and 91.16% since Decision Stump lacks sufficient complexity to harness all the discriminative potential of BPPF and ACCF features. The most accurate combination of BPPF with Naïve Bayes demonstrates a notable performance increase when utilized instead of less complex classifiers like Decision Stump according to the interpretation.

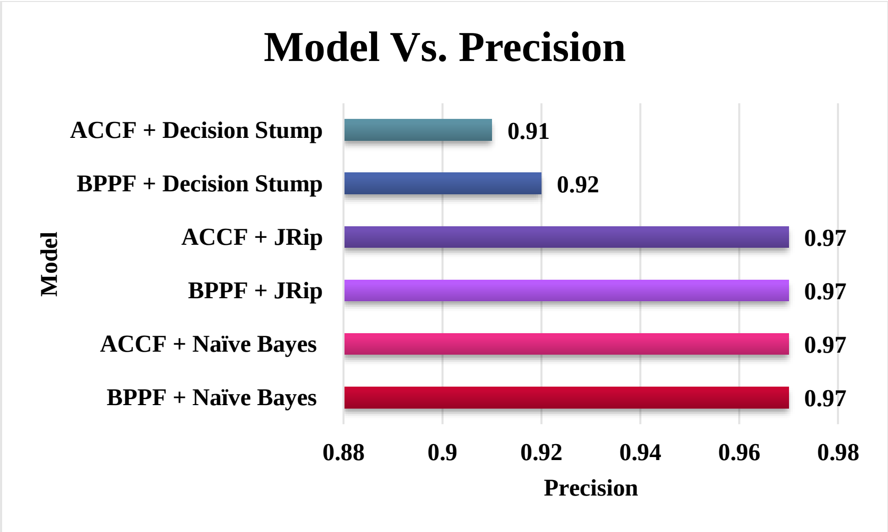


Figure 3: Model Vs Precision

The above figure 4 shows BPPF+Naïve Bayes and ACCF+Naïve Bayes demonstrated the best precision level of 0.97 because they generate minimal false positive outcomes. BPPF combined with JRip and ACCF together using JRip reached a precision score of 0.97 which indicates exceptional rule-learning abilities of JRip when paired with both BPPF and ACCF features.

The precision rate of BPPF+Decision Stump reached 0.92 indicating moderate incorrect positive predictions but ACCF+Decision Stump demonstrated poor precision at 0.91.

The precision results indicate that both Naïve Bayes and JRip classification methods demonstrate superior performance than Decision Stump regardless of feature selection thus making them appropriate choices when false positives need to be minimized.

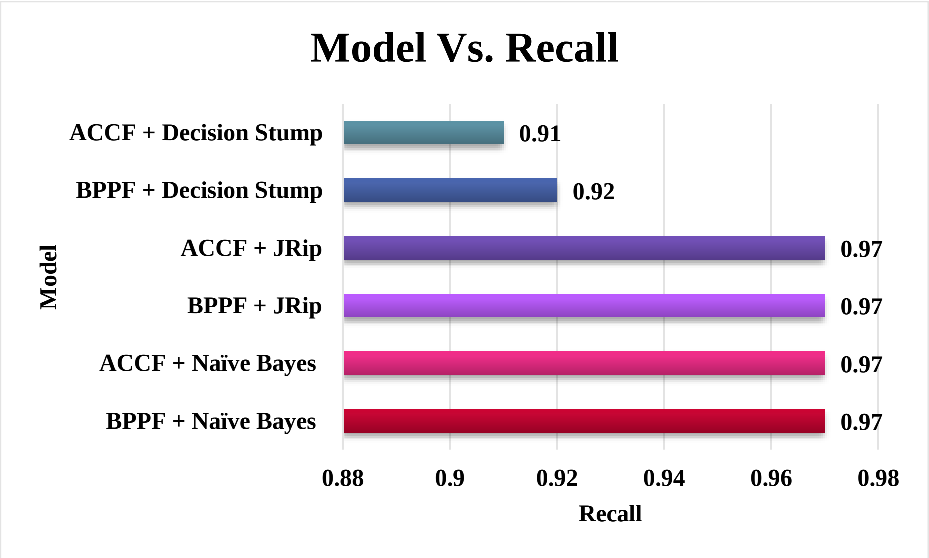


Figure 4: Model Vs Recall

The figure 4 shows BPPF+Naïve Bayes, ACCF+Naïve Bayes, BPPF+JRip, and ACCF+JRip achieved an outstanding recall performance of 0.97 that demonstrates their ability to minimize false negative predictions. The evaluation indicates Naïve Bayes and JRip classifiers demonstrate strong sensitivity when detecting useful cases among both features sets.

The recall measure of BPPF+Decision Stump reached 0.92 yet was lower than other methods while ACCF+Decision Stump had the lowest at 0.91 which indicated this combination yielded fewer correct positive detections than its peers.

The recall data presented in the chart indicates Naïve Bayes and JRip achieve the best performance for classification purposes which results in high prediction accuracy levels. These classifiers are ideal for scenarios requiring complete detection of positive situations because they show remarkable sensitivity to identify every case. For instance they work efficiently in medical diagnosis and fraud discovery operations.

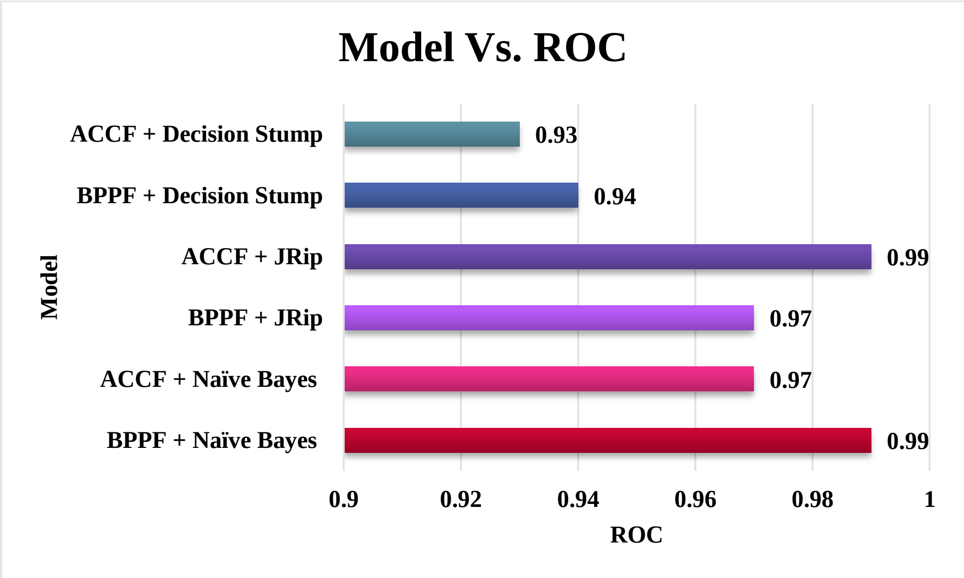


Figure 5: Model Vs ROC

The figure 5 shows that the combination of ACCF with JRip and BPPF utilizing Naïve Bayes produces highest ROC values of 0.99 which demonstrates their remarkable skill to separate data classes. The highest reliability level of these models is adequate for crucial situations requiring exceptional sensitivity and specificity. The ROC scores of BPPF+JRip and ACCF+Naive Bayes come at 0.97 demonstrating strong performance while they demonstrate a reduced capability to differentiate true and false positives in comparison to leading models. The ROC values for BPPF+Decision Stump reach 0.94 but ACCF+Decision Stump records a slightly lower score of 0.93 which indicates less efficient class differentiation.

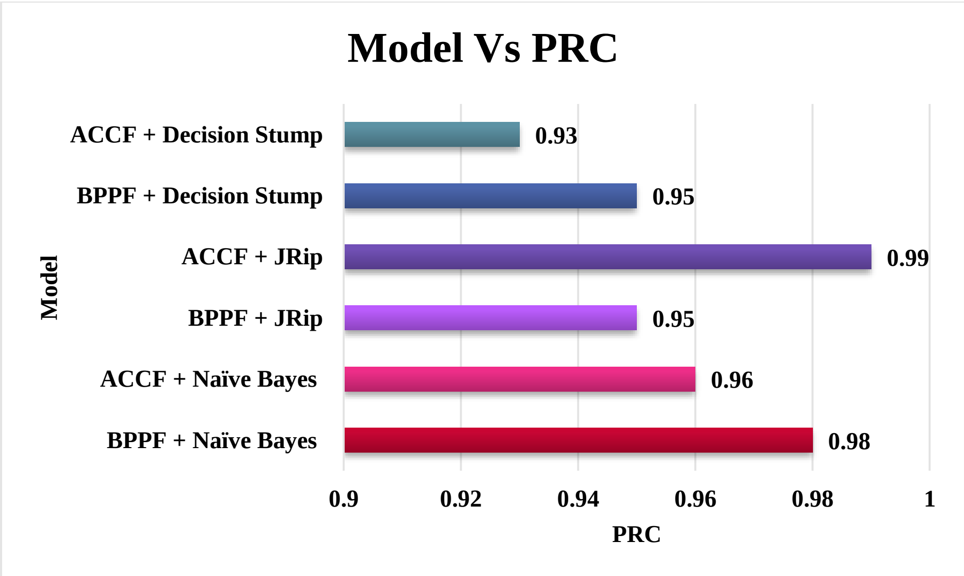


Figure 6: Model Vs PRC

The figure 6 shows that the ACCF+JRip demonstrates outstanding performance in PRC evaluation with 0.99 as its highest value which demonstrates excellent precision and recall maintenance benefits crucial for situations where false positive detection must be minimized. The combination of BPPF with Naïve Bayes shows remarkable performance in the PRC analysis by obtaining a value of 0.98 to identify relevant instances effectively while maintaining a low false alarm rate. The accuracy rates of ACCF+Naïve Bayes indicate successful data classification in imbalanced datasets with a performance score of 0.96.BPPF+JRip along with BPPF+Decision Stump maintain strong PRC scores at 0.95 which demonstrates their reliable precision-recall balance but show less optimal performance than leading methods.ACCF+Decision Stump demonstrates a PRC value of 0.93 which indicates its less efficient performance regarding the control of both false positives and false negatives in class imbalanced situations.

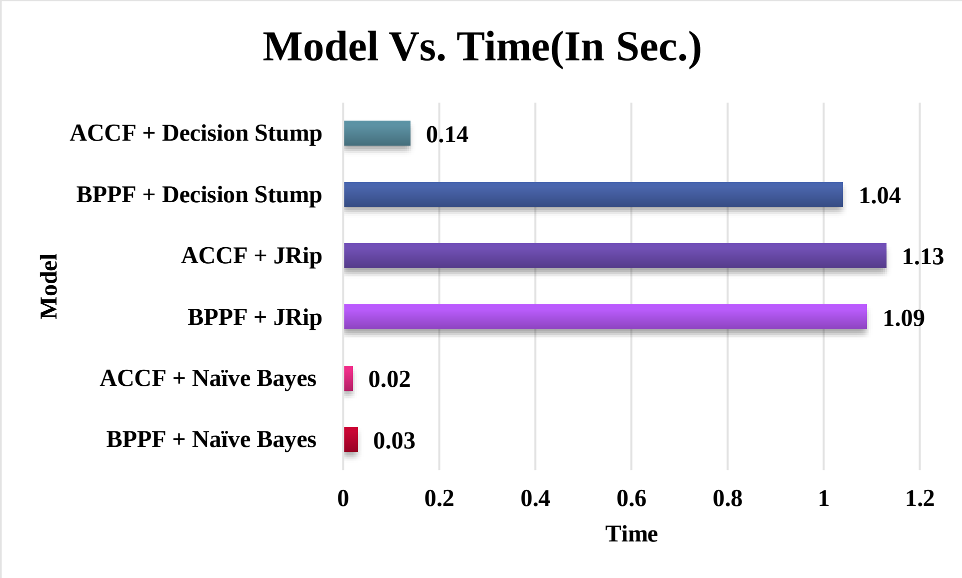


Figure 7: Model Vs Time (In Sec.)

The figure 7 shows that the fastest model for the analysis was ACCF+Naive Bayes since its processing took just 0.02 seconds until completion while BPPF+Naive Bayes ran at 0.03 seconds. These efficient models serve time-sensitive applications because they require minimal latency in their operations. The ACCF+Decision Stump model delivers good speed performance by needing only 0.14 seconds in operation which provides a quick prediction capability with modest accuracy levels.BBPF+Decision Stump and BPPF+JRip alongside ACCF+JRip require 1.04 to 1.13 seconds of total execution time. Real-time systems along with edge computing environments face limitations from these models because their increased computational requirements reduce their feasibility.Naïve Bayes-based models demonstrate the fastest computational time thus making them suitable for real-time applications yet JRip and Decision Stump-based configurations maintain their accuracy but operate best when processing data offline in non-time-sensitive scenarios.A performance and efficiency analysis of different classifiers implemented with BPPF and ACCF features produces significant finding patterns. When combined with Naïve Bayes, the BPPF feature set produced an accuracy rate of 97.28% which stood as the superior result among all tested combinations yet maintained excellent precision, recall (0.97 each) and ROC detection (0.99) for highly reliable classification. This model demonstrates high PRC score of 0.98 as well as robustness while processing data in only 0.03 seconds which makes it ideal for real-time usage. ACCF+Naïve Bayes offered 97.02% accuracy combined with 0.97 precision and recall performance at the lowest 0.02 seconds execution time to make it the fastest approach.JRip models produced similar results in rule-based classification accuracy and all key metrics reached 0.97 for precision and recall as well as ROC assessment. The ACCF+JRip model outperformed BPPF+JRip in PRC (0.99 vs 0.95) and ROC (0.99 vs 0.97) scores while increasing runtime duration by a small margin to 1.13 seconds compared to 1.09 seconds.The Decision Stump models showed inferior results compared to other models. The performance of BPPF+Decision Stump reached 92.02% accuracy while ACCF+Decision Stump achieved 91.16% accuracy. These models performed less accurately with recall and precision values between 0.91 to 0.92 while requiring execution times of 1.04s and 0.14s making these methods inappropriate for highly precise applications.

5. CONCLUSIONS

The research employed Naïve Bayes and JRip with Decision Stump as lightweight machine learning classifiers to pair with Binary Patterns Pyramid Filter (BPPF) and Auto Color Correlogram Filter (ACCF) handcrafted feature extraction methods for identifying plant diseases using the PlantVillage dataset. Results showed that Naive Bayes combined with BPPF obtained the best classification outcomes with 0.03-second execution time and 97.28% accuracy and precision and recall scores near 0.97–0.99. The ACCF+Naïve Bayes configuration achieved 97.02% accuracy while processing data at 0.02 seconds thus making it ideal for time-sensitive real-time operations. Models built with JRip and the combination of ACCF and BPPF features achieved performance at 96.9% accuracy but processed information at durations longer than one second. JRip models provide interpretability but their offline use remains optimal because they execute slowly. Models based on Decision Stumps showed the most inferior accuracy performance (~91–92%) when compared to other configurations since they failed to detect intricate discriminative patterns across features. The low computation times of Decision Stump classifiers do not match their limited value for precision-critical applications because of their inferior predictive capabilities. Naïve Bayes classifiers integrated with ACCF or BPPF features deliver an effective minimalistic technique for identifying plant diseases based on the research findings.

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